Introduction

Salt domes are often of important geologic implications for robust characterization and interpretation of hydrocarbon reservoirs in the subsurface, and the presence of a salt body can be easily recognized from 3D seismic data due to the relatively weak and chaotic reflection inside the salt. However, computer-aided salt body detection and interpretation is challenging, especially in the exploration areas of multiple salt bodies developed at different stages. In the past decades, great efforts have been devoted into resolving this challenging, including extracting salt attributes and developing salt-detection methods/algorithms for fully- or semi-automatic detection of salt bodies.

From the perspective of seismic attribute analysis, the most recent salt attributes are the gradient of textures (GoT) (Shafiq et al., 2015a), the seismic saliency (Shafiq et al., 2016), and the salt likelihood (Wu, 2016). In addition, the gray-level co-occurrence matrix (GLCM) is also widely used for seismic facies analysis as well as salt dome detection (e.g., Gao, 2003; Eichkitz et al., 2013). Meanwhile, even though initially developed for seismic fault interpretation, the geometric attribute is also applicable to the salt boundary detection by evaluates how the seismic signal changes laterally, including the coherence as well as its derivatives (e.g., Bahorich and Farmer, 1995; Marfurt et al., 1998), the curvature (e.g., Roberts, 2001; Al-Dossary and Marfurt, 2006; Di and Gao, 2016a), and the flexure (e.g., Gao, 2013; Gao and Di, 2015; Di and Gao, 2016b; Yu and Li, 2017). Based on the maps generated by these attributes, the salt boundaries have been differentiated from the surrounding non-boundary features. Correspondingly, the salt boundary extraction in such an attribute image could be considered as an image segmentation problem, and various approaches have been presented in practices, including the normalized cuts image segmentation (Lomask et al., 2007), the active-contour-models method (Shafiq et al., 2015b), and the sparse representation (Ramirez et al., 2016).

In this paper, we propose a new method for accurately detecting the boundary of salt bodies based on multi-attribute k-means cluster analysis, which consists of two major components. First, a suite of seismic attributes is selected and calculated from the amplitude volume to help differentiate the salt boundaries from the surrounding non-boundary features. Second, the k-means clustering is applied in the attribute domain and generates a probability volume that highlights the salt boundaries. Finally, we demonstrate the added values of the proposed method through applications to the F3 seismic dataset over the Netherlands North Sea, where multiple salt domes are observed in the subsurface.

Methodology

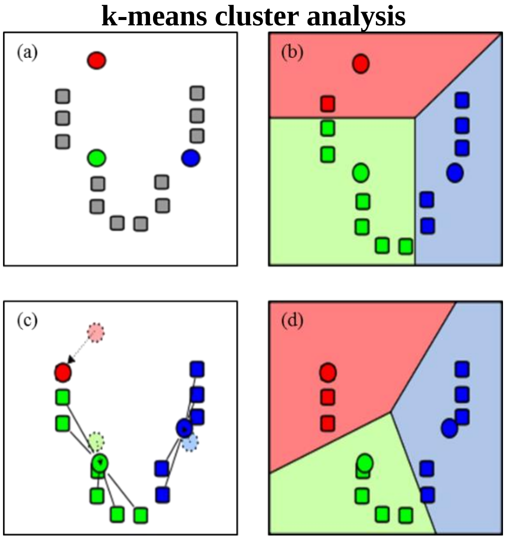

Figure 1 *The cartoon illustration of the k-means clustering of twelve observations into three clusters*

The k-means cluster analysis (MacQueen, 1967) was first developed in the field of signal processing with great applications in data mining, which is capable of partitioning the observations into k clusters with the shortest distance between the observations and their associated cluster centres. Take a given dataset of twelve observations for example (denoted by squares in Figure 1). In the data domain, the k-means cluster analysis consists of four steps, First, the number of clusters k (in this case k=3) is specified with their centres initialized either randomly or manually (denoted by colour circles in Figure 1a). Second, every observation is tentatively assigned to the nearest cluster in the least-squares sense, and correspondingly, the twelve observations are partitioned into three clusters. Third, with the observations incorporated into the clusters, the centres are updated by calculating the means of the new data clusters (denoted by arrows in Figure 1c). Finally, the second and third steps are repeated until convergence has been reached with no changes in the clusters, leading to the k-means model that partitions the twelve observations into three clusters (denoted by colour squares in Figure 1d).

In this study, we adapt the general k-means algorithm to work for the specific purpose of salt boundary delineation from 3D seismic data, which consists of four steps. First, twelve seismic attributes are generated from the amplitude volume, including RMS amplitude, GLCM texture (Gao, 2003; Eichkitz et al., 2013; Di and Gao, 2016c), Gradient of textures (GoT) (Shafiq et al., 2015a), Seismic saliency (Shafiq et al., 2016), and Canny edge detection (Di and Gao, 2014). Second, two sets of points are manually picked, including 197 pickings on the salt boundaries and 682 pickings on the non-boundary features. Third, the k-means cluster analysis is performed on the manual pickings and build a k-means model. Finally, the k-means model is applied to the whole seismic volume and generate a probability volume of the boundary of the salt domes.

Results

We use a subset of the F3 seismic volume over the Netherlands North Sea as the testing dataset to demonstrate the results of the proposed salt-boundary detection method. Figure 2 displays the amplitude in the vertical section of inline 415, in which the salt dome is clearly imaged with its boundary of strong reflection intensity, resulting from the apparent contrast in the acoustic impedance between the salt domes and the overlaying formation/layers. Figure 3 displays the corresponding section of salt-boundary probability, in which the salt boundaries are clearly delineated in high probability.

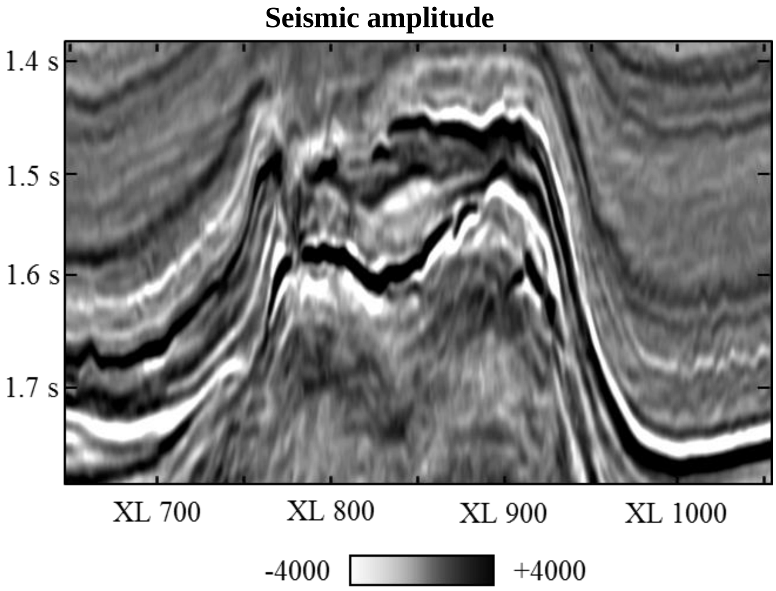

Figure 2 *The amplitude of the vertical section of inline 415 from the F3 block used for illustrating the proposed salt-boundary delineation method based on multi-attribute k-means cluster analysis.*

The probability volume not only clearly detect the salt boundaries in 3D space, but also reveals more details for understanding the salt dome, which makes it possible for post-processing of salt-dome detection, such as salt surface/body extraction. As demonstrated in Figure 4, the good match between the extracted surface and the original seismic images helps verify the accuracy of the new salt-boundary detection method proposed in this study; moreover, a salt surface could be readily extracted from the probability volume for structural framework modelling in this area, by fitting a surface of local maximum salt-boundary probability.

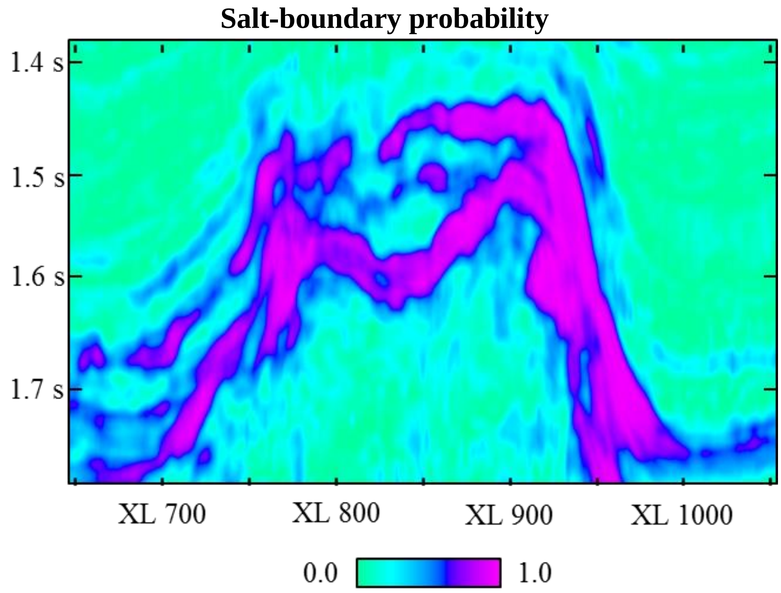

Figure 3 *The probability map of the salt boundaries generated by the proposed multi-attribute k-means cluster analysis for salt boundary detection.*

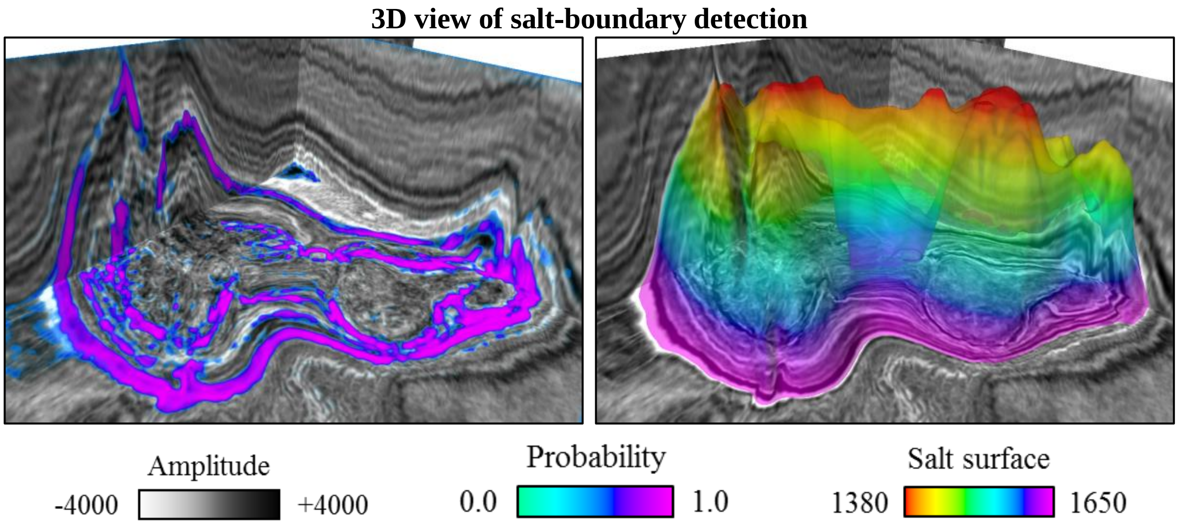

Figure 4 *3D view of the detected salt boundaries (left) and the extracted salt surface (right) from the probability volume by the proposed multi-trace k-means cluster analysis.*

Conclusions

Reliable delineation of subsurface salt bodies from 3D seismic data is essential for hydrocarbon reservoir characterization and interpretation. This study has presented a new method for salt boundary detection based on multi-attribute k-means cluster analysis, which consists of two major components. First, a suite of seismic attribute is selected that help differentiate the salt boundaries of interpretational interest from the surrounding non-boundary features. A limited number of attributes are used in this study, including RMS amplitude, GLCM texture, gradient of textures (GoT) and Seismic saliency. Such step could be further improved by developing and incorporating more salt attributes. However, it might increase the computational time. Second, the k-means cluster analysis is performed in the attribute domain and generates a probability volume, which not only clearly depicts the salt boundaries, but also holds the potential for assisting more advanced salt interpretation, such as salt surface/body extraction.

Acknowledgements

This work is supported by the Center for Energy and Geo Processing at Georgia Tech and King Fahd University of Petroleum and Minerals. Data from the North Sea was downloaded from the OpendTect Open Seismic Repository (opendtect.org/osr), where it is available under a creative commons BY-SA 3.0 license. The k-means clustering algorithm is provided by the Turi GraphLab Create™ under an academic license

References

Al-Dossary, S., and Marfurt, K. J. [2006] 3D volumetric multispectral estimates of reflector curvature and rotation. *Geophysics*, **71**, 41-51.

Bahorich, M., and Farmer, S. [1995] 3-D seismic coherency for faults and stratigraphic features. *The Leading Edge*, **14**, 1053-1058.

Di, H., and Gao, D. [2014] Gray-level transformation and Canny edge detection for 3D seismic discontinuity enhancement. *Computers & Geosciences*, **72**, 192-200.

Di, H., and Gao, D. [2016a] Improved estimates of seismic curvature and flexure based on 3D surface rotation in the presence of structure dip. *Geophysics*, **81**, IM37-IM47.

Di, H., and Gao, D. [2016b] 3D seismic flexure analysis for subsurface fault detection and fracture characterization. *Pure and Applied Geophysics*, doi:10.1007/s00024-016-1406-9.

Di, H., and Gao, D. [2016c] Improved seismic texture analysis based on non-linear gray-level transformation: *86th SEG Technical Program Expanded Abstracts*, 2093-2097.

Eichkitz, C. G., Amtmann, J. and Schreilechner, M. G. [2013] Calculation of gray level co-occurrence matrix-based seismic attributes in three dimensions. *Computers & Geosciences*, **60**, 176-183.

Gao, D. [2003] Volume texture extraction for 3D seismic visualization and interpretation. *Geophysics*, **68**, 1294–1302.

Gao, D., and Di, H. [2015] Extreme curvature and extreme flexure analysis for fracture characterization from 3D seismic data: New analytical workflows and geologic implications. *Geophysics*, **80**, IM11-IM20.

Gao, D. [2013] Integrating 3D seismic curvature and curvature gradient attributes for fracture detection: Methodologies and Interpretational implications. *Geophysics*, **78**, O21-O38.

Lomask, J., Clapp, R. G. and Biondi, B. [2007] Application of image segmentation to tracking 3D salt boundaries. *Geophysics*, **72**, P47– P56

MacQueen, J. [1967] Some methods for classification and analysis of multivariate observations: in L. M., LeCam, and J. Neyman, eds., Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, University of California Press, 281-297.

Marfurt, K. J., Kirlin, R. L. Farmer, S. H. and Bahorich, M. S. [1998] 3D seismic attributes using a running window semblance-based algorithm. *Geophysics*, **63**, 1150-1165.

Ramirez, C., Larrazabal, G. and Gonzalez, G. [2016] Salt body detection from seismic data via sparse representation. *Geophysical Prospecting*, **64**, 335–347

Roberts, A. [2001] Curvature attributes and their application to 3D interpreted horizons. *First break*, **19**, 85-100.

Shafiq, M. A., Wang, Z., Amin, A., Hegazy, T., Deriche, M., and AlRegib, G. [2015a] Detection of salt dome boundary surface in migrated seismic volumes using gradient of textures. *85th SEG Technical Program Expanded Abstracts*, 1811-1815.

Shafiq, M. A., Wang, Z. and AlRegib, G. [2015b] Seismic interpretation of migrated data using edge-based geodesic active contours. *GlobalSIP*, 596-600.

Shafiq, M. A., Alshawi, T. Long, Z. and AlRegib, G. [2016] SAISI: A new seismic attribute for salt dome detection. *ICASSP*, 1876-1880.

Wu, X. [2016] Methods to compute salt likelihoods and extract salt boundaries from 3D seismic images. *Geophysics*, **81**, IM119-IM126.

Yu, J., and Li, Z. [2017] An improved cylindrical surface fitting-related method for fault characterization. *Geophysics*, **82**, O1-O10.